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Identifying the Vulnerable to Poverty from Natural Disasters

The Case of Typhoons in the Philippines

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Abstract

This paper builds on the existing literature assessing retrospectively the quantitative effects of natural disasters on different dimensions of household welfare, to make progress toward the ex ante identification of households that are vulnerable to poverty due to natural disasters, especially typhoons. A wind field model for the Philippines is employed to estimate local wind speeds at any locality where a tropical typhoon directly passes over or nearby. The estimated wind speeds are merged with the household Family Income and Expenditure Surveys at the barangay level, and consumption expenditures are then regressed against wind speed (or a related damage index) and household socioeconomic characteristics. The estimated coefficients from the regression model are then used to estimate ex ante household vulnerability to poverty (the likelihood that household consumption falls below the poverty line) in the event of future natural disasters of different intensities.

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Identifying the Vulnerable to Poverty from Natural Disasters: The Case of Typhoons in the Philippines

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1. Introduction and Motivation

With 60% of its population living in coastal areas, and sensitivity to the El Niño phenomenon, the Philippines is one of the countries with a high propensity to be exposed to typhoons and one of the top 10 countries worldwide at risk for both climate change and disasters. Forecasts on climate change predict an increase in extreme rainfall in the Philippines, with the number of days with heavy rainfall (greater than 200mm) expected to increase with global warming by the year 2020 and 2050 (Cruz et al., 2017 Philippine Climate Change Assessment).

Understandably, given their disruptive and destructive power, typhoons attract a lot of attention in the Philippines. For instance, as recently as September 2018, Typhoon Mangkhut struck the Philippines after thousands of people evacuated their homes to dodge the 550-mile wide storm as it roared across the Pacific with maximum sustained winds of 120 miles per hour (New York Times, Sep 14, 2018).[1] Fortunately, Typhoon Mangkhut hit an area far less densely populated and, because of geography, much less vulnerable than Tacloban, a highly urbanized Philippine city devastated by Typhoon Haiyan, that struck in 2013 and resulted in 6000 deaths and destroyed so many homes across the central Philippines (Visayas) that it displaced nearly four million people.

Empirical evidence has shown that natural disasters, such as typhoons and cyclones, play an important role in preventing people from moving out of poverty and in pulling back into poverty people who were able to escape poverty. Disaster risk response is therefore an important component of poverty reduction, especially in the context of recurrent shocks. With the increased focus on fragility, transient poverty, disaster risk management and crisis response, the components of an effective disaster risk management program of countries subject to frequent natural disasters are twofold: ensuring that (i) that there is immediate liquidity in the aftermath of the disaster and (ii) there is a set of scalable social protection programs in place leveraging on existing social protection systems to rapidly provide support to the exposed and vulnerable sections of the population immediately after a disaster.

Fortunately, the Philippines has one of the most advanced Social Protection systems in the East Asia Pacific region, designed to help poor households manage risk and shocks. Undergoing rapid and comprehensive social welfare reform since 2007, the Government of the Philippines has developed a number of national social protection programs that are accompanied by advanced information and delivery systems. Among them is the large conditional cash transfer program, called Pantawid Pamilya Pilipino Program (4Ps). Households receive cash grants if children stay in school and get regular health check-ups, have their growth monitored, and receive vaccines. Pregnant women must get pre-natal care, with their births attended to by professional health workers. Started in 2007, the government expanded the program to reach a total of 20 million Filipinos belonging to 4.4 million households in June 2018. The program benefits about 20% of the population, the majority of the nation's poor.

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[1] https://www.nytimes.com/2018/09/14/world/asia/typhoon-mangkhut-philippines-hong-kong.html

Nine million children are currently benefiting from the program, 1.9 million of which are in high school.

Currently, the targeting for eligibility for the benefits of the 4Ps program is aimed primarily towards alleviating chronic poverty among eligible poor households and not towards identifying those that are vulnerable to poverty. Beneficiaries are objectively selected through the National Household Targeting System, also known as *Listathanan*, which is based from a survey of the physical structure of their houses, the number of rooms and occupants, their access to running water, and other factors affecting their living conditions (Velarde, 2018). The program has one of the most comprehensive poverty targeting databases in the world today, covering 75% of the country's population. It has been used extensively to identify poor and near-poor beneficiaries for national and local government programs.

The rationale of scalable social protection programs is to expand coverage in the event of a disaster to include not only the poor but also some of those believed to be vulnerable to falling into poverty when exposed to a shock. The objective is to mitigate the direct impact on household asset and welfare losses in the direct aftermath of a disaster, but also to prevent some of the intermediate term impacts – including forced displacement, and negative coping mechanisms used by poor households to handle the shock – such as selling off productive assets.

This paper builds on the existing literature assessing *ex-post* the quantitative effects of natural disasters on different dimensions of household welfare (e.g. Anttila-Hughes and Hsiang, 2013; Strobl, 2019; Ishizawa and Miranda, 2016) to make progress towards the *ex-ante* identification of households vulnerable to poverty due to natural disasters. A wind model for the Philippines is employed to estimate local wind speeds at any particular locality where a tropical typhoon directly passes over or nearby. The estimated wind speeds are merged to the household FIES survey at the barangay level and consumption expenditures are regressed against windspeed (or a related damage index) and socioeconomic household characteristics. The paper shows that different specifications of typhoon effects have negative impacts on consumption levels, especially food. The estimated coefficients from the regression model are then used to estimate *ex-ante* household vulnerability to poverty in the event of future natural disasters of different intensity.

The proposed approach applied to the case of typhoons is fully complementary to the proxy-means targeting (PMT) method used by *Listahanan* and the 4Ps, in the sense that in addition to the chronic poor currently identified by the PMT method of the 4Ps program, it allows identification (or targeting) of the households that are likely to fall below the poverty line in the event of a natural disaster shock. The *ex-ante* identification of those who are vulnerable to poverty combined with timely support for these households makes it possible to provide targeted support in a timely and cost-effective manner.

2. Methodology

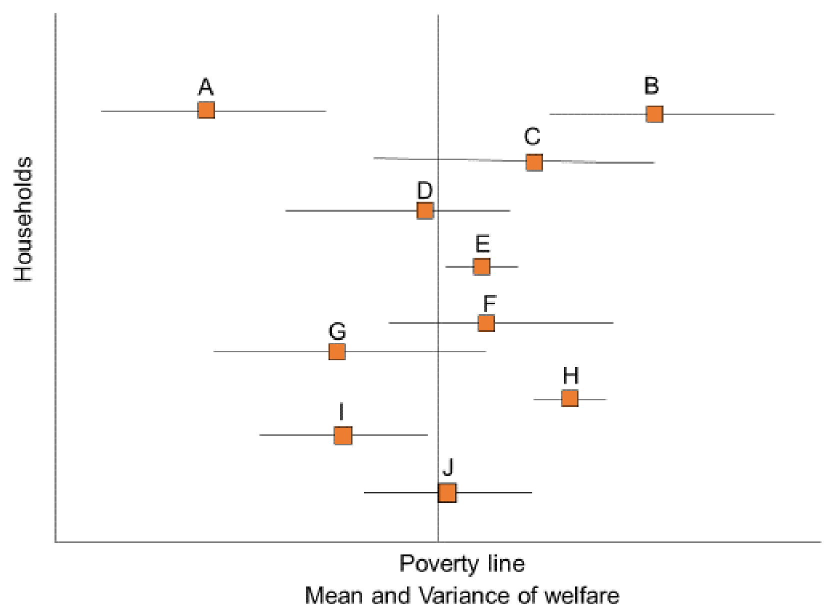
Poverty is related but different from vulnerability. The poverty status of a household is the realization of a stochastic process that generates consumption outcomes. If realized consumption or current period per capita expenditures (PCE) fall below the poverty line, the household is classified as a poor household. Thus, poverty is a backward-looking or an ex-post measure of household well-being that may have been affected adversely by shocks experienced in the recent or more distant past. The conceptual distinction between poverty and vulnerability to poverty, rests on the fact that vulnerability to poverty is not about the present but rather about the future (Gallardo, 2018). Vulnerability is a forward-looking or ex-ante measure of well-being summarizing the future prospects of a household, as well as something about its current well-being. The uncertainty that households face about the future stems from multiple sources of risk—natural disasters may happen, harvests may fail, food prices may rise, the main income earner of the household may become ill.

With these considerations in mind, the welfare of a household measured by PCE, is assumed to be characterized by two key parameters: the mean value of household PCE over different states of the world, and the variance of household PCE. Thus, households are assumed to differ with respect to the mean level of their PCE and the variance of their PCE around that mean.

Figure 1 summarizes these two dimensions of welfare, mean and variance, for 10 hypothetical households (households A, B, … , J). The mean consumption expenditure of a household (or the average value of consumption expenditures, for example, associated with many different shocks or states of the world over time) is depicted by the orange square. Different shocks at different points in time lead to variation around the mean value of expenditure, and the variance of welfare is depicted by the width of the horizontal lines to the right and to the left of the mean value of expenditure. Thus, households differ with respect to the mean level of their expenditure and the variance of their expenditure around that mean, with some households having a low (or high) mean level of consumption and a low (or high) variance of consumption.

Household A, for example, is on average a poor household with a low mean consumption placing it below the poverty line, depicted by the vertical line in Figure 1, whereas household B is on average a non-poor household with a higher level of mean consumption located above the poverty line. In Figure 1 below, households A, D, G and I are on average poor households and their vulnerability is "poverty induced" meaning that it is determined primarily by low endowments of assets and human capital, that are the primary determinants of their low mean value of welfare. Households B, C, E, F, H and J are on average non-poor households as their mean welfare is above the poverty line. However, some of these households are vulnerable to poverty while others are not. Households B, E and H, for example, have variability in their consumption but the variance line never crosses the poverty line. In contrast, households C, F, and J may end up below the poverty line under some circumstances, as depicted by the fact that the variance of their consumption around the mean crosses the poverty line. For households C, F, and J, vulnerability to poverty is "risk induced".[2] In general, the extent of vulnerability to poverty depends on the risk management strategies of households and communities, the abilities of households to cope after the incidence of the shock (e.g. assets owned, herd size, social capital), and access to safety nets (e.g. 4Ps).[3]

Figure 1: Vulnerability to poverty characterized by the mean and variance of welfare



An understanding of the causes of vulnerability to poverty is necessary for the design of policies that increase the overall resilience of household welfare to shocks. To the extent vulnerability to poverty is "poverty induced" (i.e., low assets and human capital endowments)

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[2] Figure 1 is also useful as an example of the difference between poverty and vulnerability headcount measures. The poverty headcount is based on the fraction of households whose consumption happens to be below the poverty line at a particular point in time. Depending on the timing of measurement and the type of shocks experienced (as well as the capacity of household to mitigate the impacts of such shocks ex ante or cope with these shocks ex post) the poverty head count may range anywhere between 20% (only households A and I poor) and 70% (households A,C,D, F, G, I, and J). In contrast, the vulnerability headcount rate is simply 70%.

[3] Vulnerability to poverty is related to the concept of "resilience" which concerns the longer time-path of well-being in the face of shocks, and especially the likelihood that any adverse outcomes of either risk avoidance or a realized shock do not persist for an extended period. For example, a nonpoor household may be vulnerable to becoming poor due to job loss yet be quite resilient if the prospects for finding follow-on employment offering similar compensation are high and/or formal or informal safety-net programs reliably provide adequate support reasonably promptly. In statistical terms, a nonpoor household with high conditional variance of income might be both vulnerable (to becoming poor) and resilient (because the poverty is sufficiently low in duration, intensity, and/or likelihood (Barrett and Constas, 2014).

then cash transfer programs or programs enhancing the delivery of basic services facilitating investments in physical and human capital are likely to be the most appropriate. The 4Ps program in the Philippines is a prime example of a cash transfer program aimed at addressing chronic or poverty-induced vulnerability. In contrast, if vulnerability is primarily "risk induced" (i.e., high uninsured income fluctuations) then an insurance type of program may be needed to increase resilience. The insurance provided would allow households to make production and investment choices based on their expected returns rather than the potential implications of these investments on welfare.

Extending some of the ideas of Hill and Porter (2017), the analytic framework adopted is operationally useful and complementary to the *Listahanan* Proxy Means Test (PMT) as well as as the (PMT+) approach summarized by Mills, Del Ninno and Leite (2015) in their survey of effective targeting mechanisms in Africa (Del Ninno and Mills, 2015). In short, the approach adopted for identifying the vulnerable consists of the following three steps:

Step 1: The mean PCE of households is estimated by a linear regression model that summarizes household welfare at any given point in time as a function household observed characteristics and the recent typhoon shock experienced. Specifically, household welfare at any given time is specified by the equation below:

$$lnC_{hbts} = ln\left(\frac{PCE_{hbts}}{CPI_{pts}}\right) = \beta_0 + \beta_1 X_{hbts} + \beta_2 W_{bts} + \gamma_r + \delta_t + \sigma_s + (\gamma_r * \delta_t) + (\gamma_r * \sigma_s) + (\delta_t * \sigma_s) + (\gamma_r * \delta_t * \sigma_s) + e_{hbts} \qquad (1)$$

where lnC_{hbts} denotes the log of real or cost-of-living-adjusted per capita expenditures (PCE) defined by the ratio the nominal PCE_{hkt},.of household *h*, in barangay or cluster *b,* in year *t*, in semester *s*, adjusted by the Consumer Price Index CPI_{pts} in province p in year *t*, in semester *s*, X_{hbts} denotes household observable characteristics, such as age and education level of the household head, the total number, age and gender composition of household members, ownership of assets such as livestock, phone radio, TV etc., characteristics of the household residence including type and quality of water and sanitation facilities, main source of energy, type of floor and material of construction for walls and roof, and W_{bts} is the typhoon-related shock experienced (proxied by the windspeed) by the barangay *b* in which the household residence is located in year *t* in semester *s*. The term γ_r denotes binary variables identifying regions (region-specific fixed effects for the 17 regions in the Philippines), δ_t denotes binary variables for year effects and σ_s denotes semester fixed effects and a full set of interactions among the three groups of fixed effects.[4] The error term e_{hbts} summarizing the influence of

[4]Thus, instead of using specific barangay variables as determinants of household consumption as done in the *Listahanan* (Velarde, 2018) the approach above uses barangay fixed effects that control for all time invariant observable and unobservable variables at the barangay-level.

all other unobservable variables and shocks on *lnC,* is assumed to be uncorrelated with included regressions and to have usual properties of a zero mean and a constant standard deviation.

There are at least two points that are important to bear in mind in relation to the above specification. First, equation (1) above is specified at the national level but in principle separate equations may be specified for urban and rural areas or for the National Capital region and all other areas in the Philippines. The analysis in this paper is carried out with the specification of equation (1) that does not take into account these refinements. Second, the specification of equation (1) above only models the direct impact of the typhoon on consumption. It is hypothesized that the direct effect of the typhoon on *ln*C summarized by the estimate of the parameter β_2 is negative ($\beta_2 < 0$).[5] In principle, one may also include the interaction of the typhoon shock with selected household characteristics summarized by X_{hbts} by including an additional term such as $\beta_3(W_{bts} * X_{hbts})$. For example, the direct effect of wind speed on welfare summarized by the estimate of the parameter β_2 may be negative but the effect of wind on consumption may be smaller for households whose residence walls or roof are constructed with cement or bricks. This effect would be captured by a positive estimate of the coefficient β_3 capturing the interaction of the wind shock with the material of walls. Such as specification will be explored in a later version of the paper.

Based on the specification above, the mean of *ln*C of each household can be estimated by the relation between their observable characteristics X_{hbts} in the absence of aggregate shocks (W_{bts}=0), i.e.,

$$E(lnC_{hbts}|\, X_{hbts}, W_{bts} = 0) = \left(\widehat{lnC_{hbts}}\right) =$$
$$= \hat{\beta}_0 + \hat{\beta}_1 X_{hbts} + \gamma_r + \delta_t + \sigma_s$$
$$+(\gamma_r * \delta_t) + (\gamma_r * \sigma_s) + (\delta_t * \sigma_s) + (\gamma_r * \delta_t * \sigma_s)$$

Step 2: The variance of household consumption (or the whiskers around the mean consumption of a household as in Figure 1) may be estimated based on the estimates of the parameters of equation (1) above, by simulating the different values of household *ln*C corresponding to different realizations of the shock and the error term. In this study, the derivation of the simulated values on household specific consumption corresponding to "future" windstorms is carried out based on the coefficient estimates of Table 1 using the historically highest value of the wind damage index f over the 1950-2016 period for the barangay where a household is located (see Figure 4a).

Given that vulnerability is about the likelihood of falling into poverty over a given time interval in the future (e.g. in period t+1) it is necessary to take into account of the potential influence of the variety of all other random shocks (in addition to windspeed) on the future value of

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[5] This is analogous to the PMT+ approach summarized in Mills, Del Ninno and Leite (2015).

PCE.[6] For this reason, 1,000 simulated values of household consumption expenditures are derived using 1,000 household specific values randomly drawn from the distribution of the error term in equation (1). The standard deviation of consumption conditional on household characteristics is then estimated based on these 1,000 simulated values of household *lnC.*

Step 3: The estimated household-specific mean and variance of *lnC* may then be used to identify the chronically poor (those whose mean consumption in the absence of a shock is below the poverty threshold) as well as those that are vulnerable to poverty from typhoons. Specifically, "chronically poor" households or households eligible for program coverage, in the absence of any shocks, are those with expected or mean *lnC*, in the absence of a shock, below the poverty threshold *z* (in log), i.e.,

$$E(lnC_{hbts}|\, X_{hbts}, W_{bts} = 0) = \left(\widehat{lnC_{hbts}}\right) \leqq\ lnz \tag{3}$$

Equation (3) may also serve as the basis for the construction of a PMT for the identification of chronically poor households outside the sample of households used for the estimation of equation (1) as is currently done in the *Listahanan* PMT of the Philippines.

The vulnerability of household *h*, in barangay *b,* in period *t+1*, in semester *s*, denoted by V_{hbt+1s}, can defined as the probability that consumption will fall below the poverty line *z*, i.e.,

$$V_{hbt+1s} = F(z) = Pr(lnC_{hbt+1s} \leq lnz) \tag{4}$$

Assuming that the distribution of real PCE for all individuals in the population is log-normal[7] expression (4) can be transformed to

$$V_{hbt+1s} = \Phi\left(\frac{lnz - E(lnC_{hbt+1s}|\, X_{hbts}, W_{bts}=0)}{\sqrt{var(lnC_{hbt+1s}|X_{hbts}, W_{bt+1s})}}\right) \tag{5}$$

[6] Hill and Porter (2017), for example, estimate the variance of consumption based on 5,000 different values of the shock drawn randomly from its historic distribution, and using a 50% threshold.

[7] It is important to bear in mind that because future probability is estimated based on data taken from the past, it must be assumed that this distribution and its parameters remain invariant in the future. Additionally, the expected value and variance of lnC in the current period is estimated based on a set of observable household characteristics. Thus, it is also assumed that the expected value and variance are the same for those who share the same observable household characteristics.

where Φ is the Gaussian standard cumulative distribution, and $E(lnC_{hbt+1s}|\, X_{hbts}, W_{bts} = 0)$ and $\sqrt{var(lnC_{hbt+1s}|X_{hbts}, W_{bt+1s})}$ are the conditional expected value and conditional standard deviation of the random variable lnC_{hbt+1s}, respectively (e.g. see Gallardo, 2018).

The above steps are not sufficient to identify a vulnerable household, since all households have a nonzero probability of falling below the poverty line. The identification of the vulnerable households requires setting a threshold for the probability of being vulnerable to poverty. For this purpose, two thresholds for vulnerability to poverty are chosen. The first, is 24.9% which is the poverty threshold in 2003.[8] In a steady state, the prevailing poverty rate may be considered as the likelihood that any household may face at being poor (e.g., see Chaudhuri, 2003). Based on this reasoning, a household is identified as vulnerable if it has a likelihood of being poor greater than or equal to the baseline poverty rate of 24.9% in 2003. The second threshold is higher, since it classifies a household as vulnerable if the household has a likelihood of being poor greater than or equal to 50%.[9]

The advantage offered by the proposed methodology is that it allows the identification of "chronically" poor households as well as of the households vulnerable to poverty due to exposure to community-level aggregate shocks (i.e., typhoons). Household welfare is defined by observable characteristics of the household and exposure to shocks. The chronically poor are identified by the relation between their observable characteristics in the absence of a shock, which is analogous to the predicting the poverty status of a household using a traditional PMT. In contrast, the vulnerable can be identified from the potential direct welfare effect of the wind speed associated with a new typhoon on future PCE and thus the possibility of falling below the poverty line.[10] One should bear in mind that an analogous similar modeling approach can be followed for the identification of the households vulnerable to other kinds of natural disasters, such as earthquakes, floods and droughts. Alternatively, if the interest is on identifying the vulnerable to all kinds of covariate and idiosyncratic shocks, and not just to a particular shock as in this paper, it would be worthwhile exploring the method proposed by Gunther and Harttgen (2009).[11]

[8] Annex 3 provides an estimate of the evolution of the poverty rate in the Philippines, based on the household PCE measure adjusted by the year/month province specific CPI used in this study.

[9] The 0.5 probability threshold is justified in the following arguments provided by Pritchett *et al.* (2000, p. 5) and by Suryahadi and Sumarto (2003, p. 48): "First, this is the point where the expected consumption coincides with the poverty line. Second, it is intuitive to say a household is "vulnerable" if it faces at least 50% probability of falling into poverty. Third, if a household is just at the poverty line and faces a mean zero shock, then this household has a one period ahead vulnerability of 0.5. This implies that, in the limit, as the time horizon goes to zero, then being *in current poverty* and being *currently vulnerable to poverty* coincide."

[10] The potential effect of the shock may also be inclusive of the interaction of the shock with other household characteristics, if the term $\beta_3(W_{bts} * X_{hbts})$ is included in equation (1).

[11] A comparison of the vulnerable identified by the two different approaches is left for a companion paper.

3. Data Sources

Household-level data: The analysis utilizes household-level data from the Philippines Family Income and Expenditure Surveys (FIES) for the years 2003, 2006, 2009, 2012, and 2015, collected by the Philippines Statistical Authority. The FIES is used for the official estimation of poverty in the Philippines and it provides detailed information on the components of household food and non-food expenditures (inside and outside the home), household income by source, as a well as a wide variety of household socio-economic characteristics.

FIES data are collected twice for each household, just after the middle of the year (July) and just following the end of the year (the following January), with responses for each survey reflecting economic behaviors over the preceding six months. Responses for each household are then averaged between the two surveys to construct annual estimates. It is important to note that if a household cannot be found in either round of the survey, it is dropped from the sample, which raises some concerns about the use of the annual FIES data made publicly available in any analysis of the welfare impacts of typhoons in general. Typhoon activity in the Philippines is concentrated in the second half of the calendar year, so estimates of typhoon impacts using consumption data averaged over two points, one in June and the other in January of next year, may be somewhat attenuated because the consumption in June is collected prior to the bulk of typhoon events and thus likely to be higher than the consumption expenditures collected in January next year.

We are fortunate to have access to the semester data behind each publicly available annual FIES survey. This offers a number of advantages: (i) it allows closer and better matching of the timing of a typhoon and the date of measurement of consumption and thus an investigation of the short-term impacts of typhoons occurring during the six month interval prior to the collection of household expenditure; and (ii) the possibility of investigating the medium-term impacts of typhons, i.e. the impacts of typhoons occurring in the first six months of the calendar year on the consumption of households in the second semester (bearing in mind that this may be biased due to attrition of households between survey rounds).

Earlier studies on the impacts of typhoons on different dimensions of welfare (Anttila-Hughes and Hsiang, 2013) have been hampered by the fact that they only had access to the annual averaged FIES consumption data, which, for the reasons mentioned above, are likely to be attenuated.[12]

The use of household-level PCE data varying across two semesters of a calendar year as well as across calendar years 2003, 2006, 2009, 2012, and 2015, and across different regions, requires taking into account of the temporal (within year and across years) and spatial variation in the cost of living in the Philippines.[13] For this reason, nominal consumption in each

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[12] This is why Anttila-Hughes and Hsiang (2013) downplay the impacts on consumption and focus on capital losses the year following typhoon exposure, as it seems unlikely that capital can be replaced immediately following a storm.

[13] The Philippines consists of 17 regions, 81 provinces and about 40,000 barangays.

year is divided by the June CPI in each province for observations in semester 1 and the December CPI in each province for observations in semester 2. [14] One notable aspect of the province-specific CPIs is that they are all equal to 100 in the base year (2012=100). This allows tracking of differences in the evolution of the cost of living across provinces over time but does not allow for identification of the difference in the cost of living across provinces in the base year.[15] The poverty line (z) used in this paper is determined using the level of PCE in 2003 corresponding to the official poverty rate of 24.9% in 2003.[16]

Shock Measure: A wind model based on Boose et al. (2004) for the Philippines is employed to estimate local wind speeds at any particular locality where a tropical typhoon directly passes over or nearby.[17]

An additional distinguishing feature of this study is the fact that it uses the Philippines Standard Geographic Codes (PSGC) of the barangays (smallest administrative units) or residence of the households sampled by the FIES. Access to the PSGC of barangays, allows the wind model to be more granular in the sense that estimates of the wind speed associated with any given typhoon can be derived for the geographic location of each barangay. This provides a much better estimate of the wind speed experienced by any given household during a typhoon and thus the basis for a more realistic assessment of the impact of wind speed on household consumption. Anttila-Hughes and Hsiang (2013), did not have access to the barangay-level codes, and thus had to estimate windspeeds at the province level. This, in turn, implies that all households in each of the 81 provinces were assigned the same wind speed irrespective of a household's distance from the typhoon's path.

Figure 2 below presents the total number of typhoons (defined as windspeeds over 119mph) by barangay between 2000-2015, whereas Figure 4, presents the total number of barangays experiencing windspeeds over 119mph by year. Clearly, moving from the southern tip of the Philippines towards the north, more and more barangays experience windspeeds over 119 mph, and many barangays in the northeastern tip of the archipelago experience such extreme windspeeds many times (up to 21 times) between 2000 and 2015 (see figure 2). Also, the number of barangays experiencing windspeeds over 119mph varies significantly by year (see figure 3).

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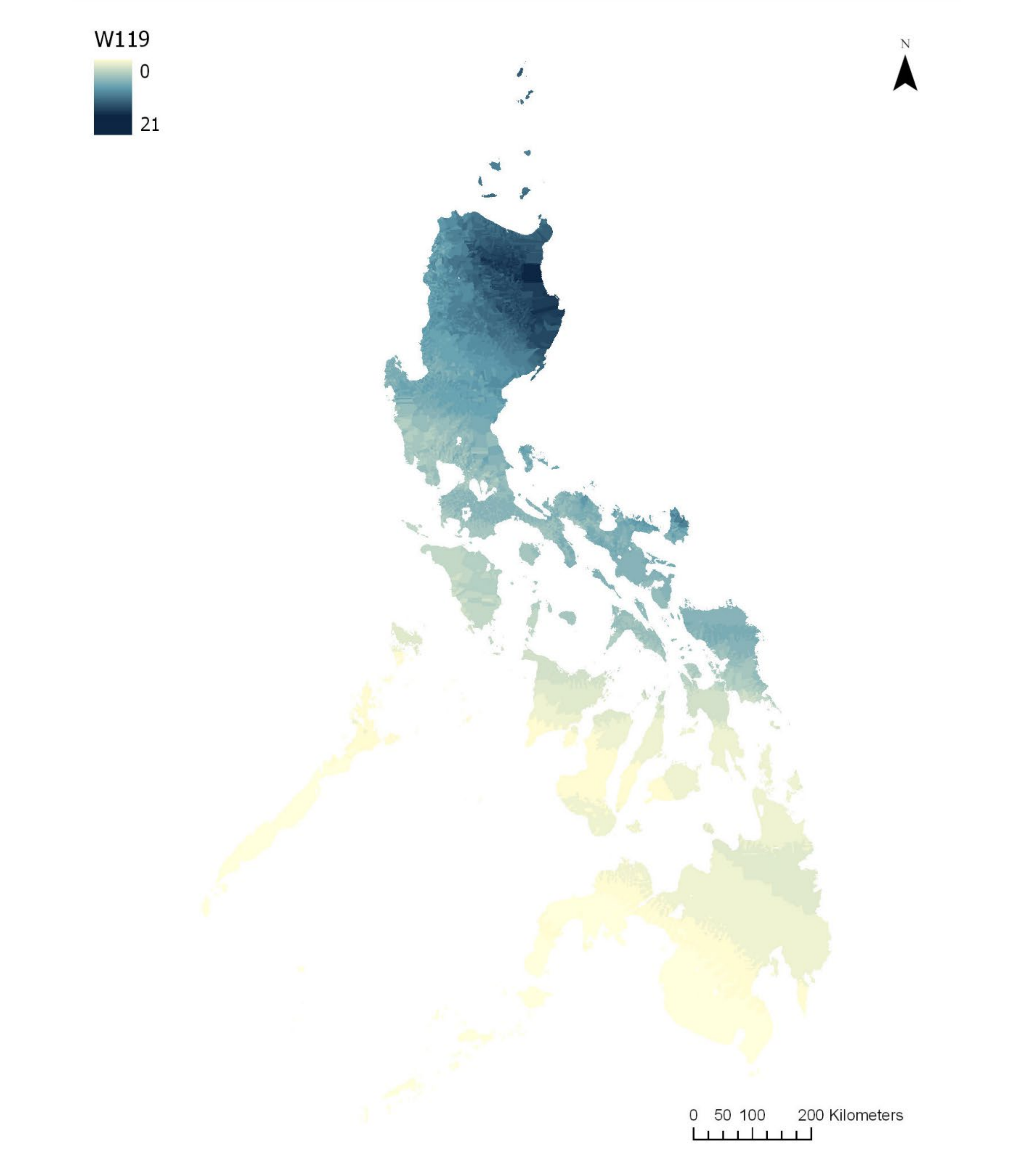
[14] The CPI by province, year, and month was downloaded from the PSA OpenStat website: http://openstat.psa.gov.ph/PXWeb/pxweb/en/DB/DB__2M/?tablelist=true&rxid=bdf9d8da-96f1-4100-ae09-18cb3eaeb313.

[15] To check the sensitivity of the estimates to a better accounting of the spatial cost of living differences, we have also tried an alternative approach that consists of first regressing the log of nominal PCE on a complete set of interactions across three sets of binary variables identifying the semester of interview of the household within a calendar year (2 in total), the year of interview (5 in total) and the region of residence (17 in total). This amounts to a total of 170 different dummy variables. The residual from such a regression is the "adjusted" lnPCE at any given point in time and region, that is expenditures comparable to the nominal expenditures in the reference time period (2003 semester 1) and region (region 1, which is the Ilocos region). The results were practically the same as to those reported in tables 1 and 2.

[16] Annex 1 provides an estimate of the evolution of the poverty rate in the Philippines, based on the household PCE measure adjusted by the year/month province specific CPI used in this study.

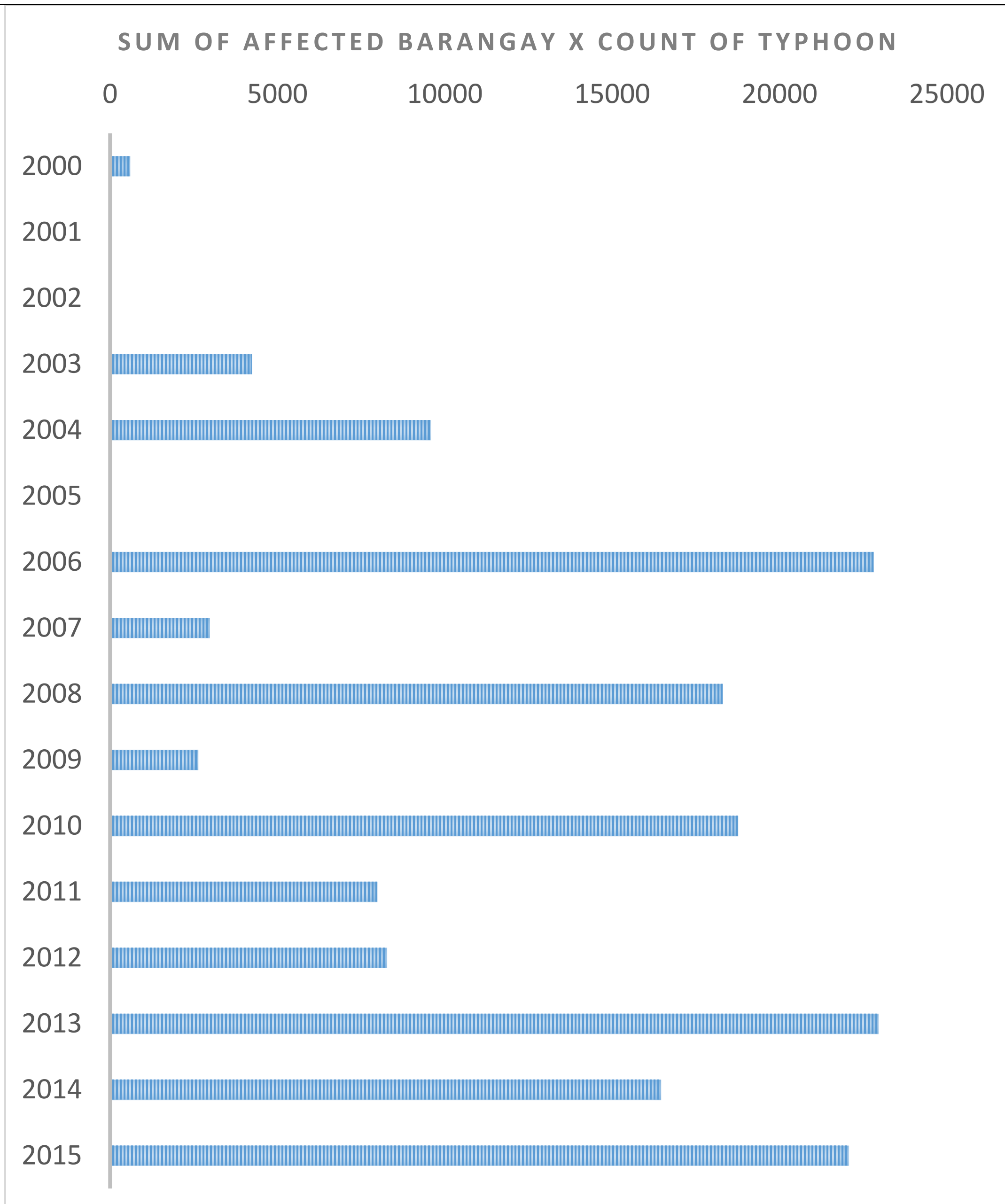
[17] A more detailed description of the wind model used is contained in Annex 2.

Figure 2: Total Number of typhoons (windspeed over 119mph) by Barangay between 2000-2015



Source: World Bank team estimates based on wind field model

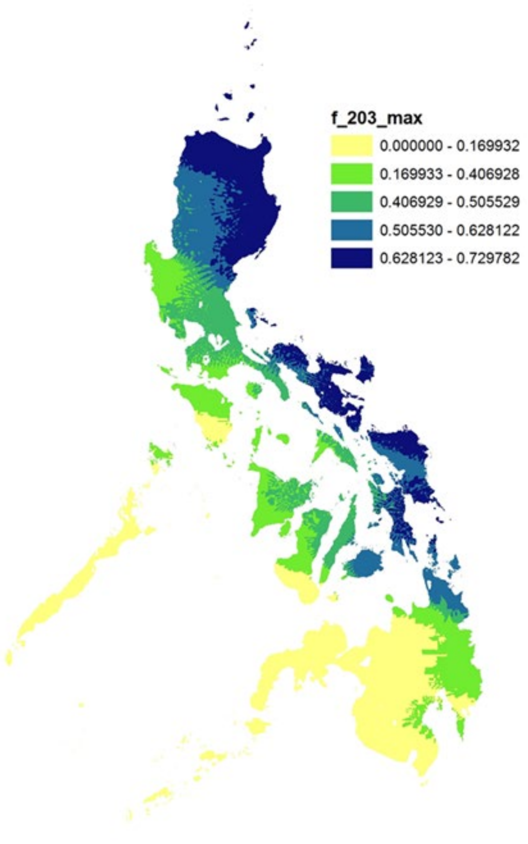
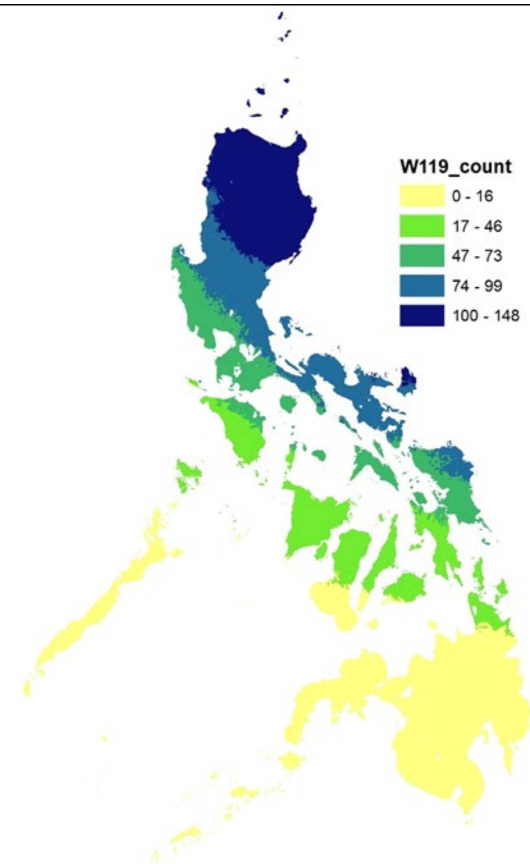
Figure 3: Total Number of barangays experiencing windspeeds over 119mph by year between 2000-2015



Source: World Bank team estimates based on wind field model

Figure 4a below presents the geographic location of the barangays with the highest value of the wind damage index over the 1950-2016 period while Figure 4b, presents the number of typhoons with windspeeds above 119 km/hr over the same period. Using these historic data and armed with the estimates of the coefficients of equation (1), the next step in the analysis is to simulate household-specific consumption associated with barangay-specific windspeeds from the historic record of typhoon storms in the Philippines over the 1950-2016 period.

Figure 4: The Philippines - Historical Incidence of Typhoons at the barangay level during the period 1950-2016

<table>
<tr><th>(a) Maximum damage index</th><th>(b) Number of typhoons with windspeed over 119 km/hr</th></tr>
<tr><td>
</td><td>
</td></tr>
<tr><td colspan="2">Source: World Bank team estimates based on wind field model and the historic record of storms over the period 1950-2016</td></tr>
</table>

4. Results

Table 1 presents the estimates of the impacts of the incidence of a typhoon on total PCE (col. 1), food and non-food expenditures per capita (col. 2 and 3, respectively), per capita expenditures on protein (col. 4), fruits (col. 5), cereals (col.6), education (col. 7) and medical services (col. 8).[18] The shock variable used is a wind damage index (denoted by f203_hy) constructed based on the maximum wind speed observed in the barangay during the 6 months preceding the month of interview of the household. Following the insights of Wang and Xu (2010) and Emanuel (2011), local destruction is allowed to vary with wind speed in a cubic manner. Specifically, based on Emanuel (2011), the wind damage index constructed is based on the expression

$$f = \frac{v_n^3}{1+v_n^3} \tag{6}$$

where f is the fraction of the property lost and

$$v_n = \frac{MAX[(W-W_{thresh}),0]}{W_{half}-W_{thresh}} \tag{7}$$

where W is the maximum wind speed in the barangay during the 6 months preceding the date of interview of the household, W_{thresh} is the wind speed above which damage occurs, assumed to be 50 knots (or 98 km/hr), and W_{half} is the wind speed at which half the property value is lost, assumed to be 203 km/hr.

Table 1: The impact of typhoons on total PCE and different components of PCE (using wind damage index)

	PCE Total (1)	PCE on Food (2)	PCE Non-Food (3)	PCE Protein (4)	PCE Fruit (5)	PCE Cereal (6)	PCE Education (7)	PCE Medical (8)
f203_hy	-0.157***	-0.235***	-0.0621	-0.483***	-0.117	-0.0453	-0.111	-0.0981
	(-3.55)	(-5.32)	(-1.09)	(-6.83)	(-1.60)	(-1.25)	(-0.78)	(-0.71)
adj. R2	0.632	0.504	0.635	0.384	0.305	0.171	0.298	0.227
N	412,286	412,268	412,286	410,242	410,149	411,118	255,586	355,402

[18] Total PCE includes both food and non-food expenditure. Food expenditure includes both food expenditure at home (bread, meat, fish, milk, oil, fruit, vegetable, sugar, coffee, mineral) and outside the home. Non-food expenditure includes alcohol, tobacco, cloth, furnishing, health, water, transport, communication, recreation, education, miscellaneous, durable, occasional, and other expenditures. Protein expenditure includes meat, milk, cheese, egg, fish, and seafood. Cereal expenditure includes rice, corn, and other cereals.

Notes: The full list of regression estimates of equation (1) is presented in Annex 2. Additional explanatory variables included but not reported here: family size, head is female, age of head, marital status of head, education level of head, head has a job, building type (single house vs, apartment etc.), type of material for roof, type of material for wall, floor area, type of toilet, water source, and separate binary variables for semester, year, and region, along with a complete set of interactions among these binary variables. Standard errors are corrected for clustering at the barangay level.

It is hypothesized that the direct effect of the typhoon on PCE summarized by the estimate of the parameter β_2 is negative ($\beta_2 < 0$). The estimate of β_2 in col. 1 of Table 1 reveals that exposure of a barangay to a typhoon in the 6 months before the month of interview is associated with a statistically significant decline in PCE. The coefficient -0.157 in col.1 of Table 1 implies that when the f index (denoted by f203_hy) is 1, which implies that there is 100% damage of the building/infrastructure, then PCE decline by 15.7 percent.[19] Along similar lines, PCE on food decline by 23.5 percent (see col. 2) while PCE on non-food are not significantly affected. Also, PCE on protein seem to be negatively affected (decline by 48.3%) whereas PCE on fruits and vegetables, cereals, education and medical services appear to be unaffected.

Table 2 below reports estimates of equation (1) including an interaction term of the windspeed variable with the household being a beneficiary of the 4Ps conditional cash transfer program (i.e., the binary variable 4Ps and the interaction term $\beta_3(W_{bts} * 4Ps)$ are included in equation (1)). This is useful for assessing whether access to the 4Ps program is associated with some protection to household welfare (as measured by PCE) from the negative effects of typhoons (at least among the current beneficiaries in the typhoon affected barangays).[20] Given that the 4Ps program was established in 2007, expanding coverage gradually over the years, the estimates in Table 2 are based on the reduced sample of households surveyed in the two most recent years of FIES in 2012 and 2015, when coverage was more extensive.

The coefficient of the binary variable 4Ps is negative and statistically significant which attests to the targeting of the 4Ps program towards the poor (i.e., households benefitting from the 4Ps program have lower PCE than those not in the program). The negative and statistically significant coefficient of the wind speed variable (f203_hy) implies that the shock has a negative effect on the PCE of nonparticipants in the 4Ps program (the reference group). The interaction of the shock with 4Ps is not statistically significant from zero but, it is positive, which suggests that the (negative) impact of the shock is smaller for 4Ps beneficiaries. In addition, the coefficient of the interaction term of the shock with 4Ps is smaller than the

[19] Alternatively, the -0.157 coefficient implies a 11.4% decline in PCE when *f*= 0.729, the value of the *f* index at the historically maximum windspeed recorded during the period 1950-2016 (0.729). Using the sample average of the non-zero maximum value of the *f* index (*f* = 0.42), total PCE declines by 6.6%, food PCE decline by 9.87% and protein PCE decline by 20.3%.

[20] As mentioned above, the present targeting system of the 4Ps is designed towards identifying the chronically poor and not necessarily those "vulnerable to poverty" from a typhoon or other natural disasters.

coefficient of the shock itself, which implies that 4Ps is able to provide only partial rather than full protection to the consumption of 4Ps beneficiaries.

Table 2: The impacts of typhoons on PCE and access to 4Ps (using wind damage index)

	PCE Total (1)	PCE on Food (2)	PCE Non-Food (3)	PCE Protein (4)	PCE Fruit (5)	PCE Cereal (6)	PCE Education (7)	PCE Medical (8)
f203_hy	-0.0856	-0.125*	-0.0371	-0.307***	-0.00294	-0.0462	-0.0203	-0.0664
	(-1.64)	(-2.44)	(-0.54)	(-3.87)	(-0.03)	(-0.99)	(-0.12)	(-0.39)
4Ps	-0.105***	-0.0731***	-0.154***	-0.160***	-0.0460***	-0.0019	-0.0705***	-0.118***
	(-20.45)	(-15.86)	(-22.52)	(-19.92)	(-5.96)	(-0.42)	(-3.96)	(-7.09)
4Ps x f203_hy	0.0612	0.0938*	0.0285	0.096	0.0519	0.049	-0.0182	-0.00051
	(1.41)	(2.31)	(0.47)	(1.35)	(0.80)	(1.06)	(-0.10)	(-0.00)
adj. R2	0.618	0.473	0.628	0.349	0.279	0.134	0.275	0.244
N	167,960	167,956	167,960	167,134	167,275	167,558	100,366	144,019

Notes: Additional explanatory variables included but not reported here: family size, head is female, age of head, marital status of head, education level of head, head has a job, building type (single house vs, apartment etc.), type of material for roof, type of material for wall, floor area, type of toilet, water source, and separate binary variables for semester, year, and region, along with a complete set of interactions among these binary variables. Standard errors are corrected for clustering at the barangay level.

Testing the robustness of the results

(i) Changing the reference period of the shock

Table 3 presents estimates of the impact of typhoons by changing the reference period over which the f index is calculated. The shock variable f203_bhy, is constructed using the maximum wind speed observed in the barangay during the first half (or the first 6 months) of the 12-month period preceding the month of interview of the household. This change in the reference period offers the opportunity to investigate the possibility of lagged effects of typhoons on the outcome variables of interest. The results in table 3 reveal that there are no significant lagged effects of typhoons on total household PCE or any of its components.

Table 3: Lagged effects of typhoons on total PCE and different components of PCE (using wind damage index)

	PCE Total (1)	PCE on Food (2)	PCE Non-Food (3)	PCE Protein (4)	PCE Fruit (5)	PCE Cereal (6)	PCE Education (7)	PCE Medical (8)
f203_hy	-0.166***	-0.246***	-0.0710	-0.494***	-0.114	-0.0485	-0.135	-0.119
	(-3.65)	(-5.44)	(-1.21)	(-6.82)	(-1.52)	(-1.31)	(-0.92)	(-0.84)
f203_bhy	-0.116	-0.132	-0.115	-0.150	0.0443	-0.0412	-0.305	-0.257
	(-1.44)	(-1.78)	(-1.03)	(-1.17)	(0.34)	(-0.59)	(-1.12)	(-0.91)
adj. R2	0.632	0.504	0.635	0.384	0.305	0.171	0.298	0.227
N	412,287	412,269	412,287	410,243	410,150	411,119	255,586	355,403

Notes: Additional explanatory variables included but not reported here: family size, head is female, age of head, marital status of head, education level of head, head has a job, building type (single house vs, apartment etc.), type of material for roof, type of material for wall, floor area, type of toilet, water source, and separate binary variables for semester, year, and region, along with a complete set of interactions among these binary variables. Standard errors are corrected for clustering at the barangay level.

(ii) Changing the shock measure

Tables 4 and 5 check the robustness of the findings in Tables 1 and 2, by using a binary variable (W119_hy), taking the value of 1 if the barangay experienced any (at least once) windspeeds over 119 km/hr during the last 6 months (or during the second half of the 12-month period) immediately preceding the month of interview of the household.

Overall the estimates in Tables 4 and 5 confirm that results reported in tables 1 and 2 are very robust. The estimate of β_2 in col. 1 of Table 4 reveals that exposure of a barangay to a typhoon in the 6 months before the month of interview, is associated with a statistically significant decline in PCE by 6.7 percent. This estimate is very comparable to the impact estimates of typhoons on PCE in the literature. For example, for the Philippines, Anttila-Hughes and Hsiang (2013) using provincial panel data, estimate a reduction between 5.9% and 7.1% in consumption, whereas Ishizawa and Miranda (2016), estimate a decline ranging between 2% and 4% for Central American countries. Baez et al. (2015) using panel data also show a fall in the consumption of Guatemalan households by 12.6%.

Along similar lines, PCE on food decline by 5.1% (see col. 2) and PCE on non-food decline by 7.8%. Also, PCE on protein seem to be negatively affected (decline by 10.1 pp) whereas PCE on fruits and vegetables, cereals, education and medical services appear to be unaffected.[21]

[21] We have also confirmed that changing the reference period of the shock measure based on the binary variable W119_bhy, does not result in any significant lagged effects of typhoons on total household PCE or any of its components (as is the case with the *f* index used in Table 3).

Table 4: The impact of typhoons on total PCE and different components of PCE (using a binary variable on wind speed)

	PCE Total (1)	PCE on Food (2)	PCE Non-Food (3)	PCE Protein (4)	PCE Fruit (5)	PCE Cereal (6)	PCE Education (7)	PCE Medical (8)
W119_hy	-0.0672***	-0.0506***	-0.0781***	-0.101***	-0.0263	-0.00818	-0.0439	-0.0401
	(-6.66)	(-5.10)	(-6.11)	(-6.00)	(-1.52)	(-1.03)	(-1.38)	(-1.34)
adj. R2	0.632	0.504	0.635	0.384	0.305	0.171	0.298	0.227
N	412,286	412,268	412,286	410,242	410,149	411,118	255,586	355,402

Notes: Additional explanatory variables included but not reported here: family size, head is female, age of head, marital status of head, education level of head, head has a job, building type (single house vs, apartment etc.), type of material for roof, type of material for wall, floor area, type of toilet, water source, and separate binary variables for semester, year, and region, along with a complete set of interactions among these binary variables. Standard errors are corrected for clustering at the barangay level.

Table 5 presents estimates including an interaction term of the windspeed binary variable with the household being a beneficiary of the 4Ps conditional cash transfer program. Qualitatively similar patterns are observed when the binary variable signifying the incidence of high wind speeds (W119_hy) is interacted with a household being a beneficiary of the 4Ps program (compare Table 5 with Table 2).

Table 5: The impact of typhoons on PCE including interactions (using a binary variable on wind speed)

	PCE Total (1)	PCE on Food (2)	PCE Non-Food (3)	PCE Protein (4)	PCE Fruit (5)	PCE Cereal (6)	PCE Education (7)	PCE Medical (8)
W119_hy	-0.064***	-0.054***	-0.066***	-0.125***	-0.0166	-0.00136	0.0352	-0.0403
	(-4.66)	(-4.04)	(-3.81)	(-5.53)	(-0.73)	(-0.12)	(0.87)	(-0.95)
4Ps	-0.104***	-0.073***	-0.151***	-0.159***	-0.042***	-0.00364	-0.050**	-0.105***
	(-19.27)	(-15.13)	(-21.13)	(-18.79)	(-5.13)	(-0.77)	(-2.70)	(-6.07)
4Ps x W119_hy	0.00318	0.0122	-0.00488	0.00569	-0.0119	0.0141	-0.098**	-0.0566
	(0.38)	(1.55)	(-0.42)	(0.43)	(-0.93)	(1.73)	(-2.85)	(-1.76)
adj. R2	0.619	0.473	0.629	0.349	0.279	0.134	0.276	0.244
N	167960	167956	167960	167134	167275	167558	100366	144019

Notes: Additional explanatory variables included but not reported here: family size, head is female, age of head, marital status of head, education level of head, head has a job, building type (single house vs, apartment etc.), type of material for roof, type of material for wall, floor area, type of toilet, water source, and separate binary variables for semester, year, and region, along with a complete set of interactions among these binary variables. Standard errors are corrected for clustering at the barangay level.

(iii) Accounting for unobserved heterogeneity

The estimates reported so far are obtained based on regional fixed effects (denoted by γ_r) that control for all the observed and unobserved time invariant region-specific characteristics. However, there may be unobserved heterogeneity at the barangay or even at the household level that can affect the estimates of the impact of the shock on welfare.

As a means of further exploring the potential role of unobserved heterogeneity on the estimates of the impacts of typhoons on welfare, Table A in Annex 5 presents estimates of equation (1) including as an additional control the historically highest value of the wind damage index f over the 1950-2016 period for the barangay where a household is located. This variable is meant to serve as a proxy for the barangay characteristics that factor in the decision of household on whether to live in a specific area. The coefficient of the impact of the f damage index increases slightly from -0.157 in Table 1 to -0.168 which suggests that barangay-level heterogeneity does not seem to have a major effect on the estimated effect of typhons on welfare.

The availability of two observations within any given year for the majority of households provides the opportunity to also investigate the role of time invariant household-specific unobserved heterogeneity. Table 6 reports the estimates of the impact of the typhoons on PCE and its components using the household random effects specification (panel 6a) as well as the household fixed-effect specification for the two different shock measures, the damage index f203-hy over the last 6 months and the binary variable W119_hy, taking the value of 1 if the barangay experienced any (at least once) windspeeds over 119 km/hr during the last 6 months.[22] The random effects estimates in panel 6a, are considerably lower in comparison to Table 1, with the coefficient of the wind damage index losing statistical significance, and the coefficient of the binary variable on wind speed decreasing from 6.7 % in Table 4 to 2.5%. The fixed-effects specification in panel 6b yields a positive, albeit insignificant effect of the damage index f203-hy over the last 6 months on PCE. The low values of the coefficients of the shocks are a likely consequence of the decreased variability in the sample associated with the fixed or random effects transformation.

[22] It is useful to bear in mind that the fixed effect method relies exclusively on within household variation over time, while ignoring variation between households. In contrast, the random effects method is a weighted average of the between and within household variation. Annex 4 also presents the random-effects and fixed-effects estimates analogous to Table 2, where the damage index f and the wind speed dummy are interacted with participation in the 4Ps program.

Table 6: The impact of typhoons on total PCE and different components of PCE controlling for household unobserved heterogeneity

6.a: Random Effects Specification

	PCE Total (1)	PCE on Food (2)	PCE Non-Food (3)	PCE Protein (4)	PCE Fruit (5)	PCE Cereal (6)	PCE Education (7)	PCE Medical (8)
Using a wind damage index:								
f203_hy	-0.0139	-0.112**	0.0423	-0.286***	-0.0379	-0.0285	-0.130	-0.0241
	(-0.38)	(-2.83)	(0.94)	(-4.66)	(-0.56)	(-0.84)	(-1.08)	(-0.19)
R2 overall	0.631	0.504	0.634	0.384	0.306	0.171	0.298	0.227
N	412286	412268	412286	410242	410149	411118	255586	355402
Using a binary variable on windspeed:								
W119_hy	-0.0251***	-0.0254**	-0.0305**	-0.0603***	-0.0138	-0.00293	-0.00810	-0.0201
	(-3.38)	(-3.11)	(-3.25)	(-4.28)	(-0.89)	(-0.42)	(-0.30)	(-0.76)
R2 overall	0.631	0.504	0.634	0.384	0.306	0.171	0.298	0.227
N	412286	412268	412286	410242	410149	411118	255586	355402

6b: Fixed effects specification

	PCE Total (1)	PCE on Food (2)	PCE Non-Food (3)	PCE Protein (4)	PCE Fruit (5)	PCE Cereal (6)	PCE Education (7)	PCE Medical (8)
Using a wind damage index:								
f203_hy	0.0633	0.00703	0.103*	-0.0718	0.0784	0.00225	-0.148	0.106
	(1.61)	(0.16)	(2.12)	(-1.07)	(1.01)	(0.06)	(-1.18)	(0.72)
R2 overall	0.298	0.252	0.303	0.208	0.187	0.115	0.0686	0.298
N	412286	412268	412286	410242	410149	411118	255586	355402
Using a binary variable on windspeed:								
W119_hy	-0.000965	0.00131	-0.00146	-0.0104	0.00685	0.00804	0.0190	0.0171
	(-0.13)	(0.15)	(-0.15)	(-0.70)	(0.41)	(1.04)	(0.65)	(0.57)
R2 overall	0.300	0.252	0.306	0.206	0.186	0.115	0.0719	0.107
N	412286	412268	412286	410242	410149	411118	255586	355402

Notes: Additional explanatory variables included but not reported here: family size, head is female, age of head, marital status of head, education level of head, head has a job, building type (single house vs, apartment etc.), type of material for roof, type of material for wall, floor area, type of toilet, water source, and separate binary variables for semester, year, and region, along with a complete set of interactions among these binary variables. Standard errors are corrected for clustering at the barangay level.

Another potential source of bias in the panel estimates above may be the possible attrition of households across semesters in the FIES. In Table B in Annex 5 we present OLS estimates analogous to those presented in Table 1 based on the sub-sample of households appearing in both semesters (i.e. excluding households who appear only in one semester). If attrition bias were a serious problem, then the estimates should differ. The estimates suggest that attrition bias is not a problem since the estimates obtained are practically identical to those in Table 1.[23]

Considering the general robustness of the estimates reported in Table 1 to all the various sources of bias, the next section proceeds with the identification of the vulnerable based on the OLS estimates of Table 1.

Identifying the chronic poor and the vulnerable

Table 7 below summarizes the profile of the households identified as non-poor vulnerable to poverty based on the analysis above based on the 24.9 % threshold for vulnerability to poverty. The estimates corresponding to table 7 based on the 50% threshold for vulnerability to poverty are contained in Annex 6. For comparison, the profile of the households identified as chronically poor and nonpoor (and nonvulnerable) to poverty is also presented. In comparison to the chronic poor, households vulnerable to poverty are a bit older, consist of higher proportion of female headed households, have generally a higher level of education (most are high school graduates), and have roofs, and walls made with stronger material and have access to electricity. The regional composition of households that are vulnerable to poverty differs from the regional composition of the chronic poor households, with a higher proportion of the vulnerable households residing in the Ilocos Region, Cagayan Valley, Central Luzon, Southern Tagalog Region, Bicol Region, especially in the Eastern Visayas Region, National Capital Region, and Cordillera Administrative Region.

Table 7: The profile of the Chronic Poor and those Vulnerable to Poverty (based on the 24.9% threshold)

Summary statistics	Total	Chronic poor (21.4%)	vulnerable to poverty (22.8%)	Non-poor (55.8%)
Total adjusted Expenditure per capita	19,283	7,214	11,685	27,004
P4 Beneficiaries	18.5%	49.2%	25.0%	5.5%
Family Size	4.73	6.49	4.92	3.97
Age of Household head	49.06	45.35	49.06	50.49
Female headed	19.50%	8.38%	15.12%	25.54%
Head marital status				
Single	4.33%	0.46%	2.08%	6.73%

[23] A logit regression was also estimated on the sample of households in the first semester, (dropout = 1, if a household does not appear in the second semester, and equal 0 otherwise) on the same set of household regressors used in equation (1) and using the highest value of the *f* index and windspeed over the two semesters in any given year. The estimates revealed that typhoons measured either as high values of the *f* index or the incidence of windspeeds above the 113 mph threshold are not significantly associated with the likelihood of household attrition out of the FIES. In contrast, some household characteristics where significantly associated with increased likelihood of attrition out of the FIES. These included having a smaller family size, being a female headed household, younger (lower age) head, and head not having a job.

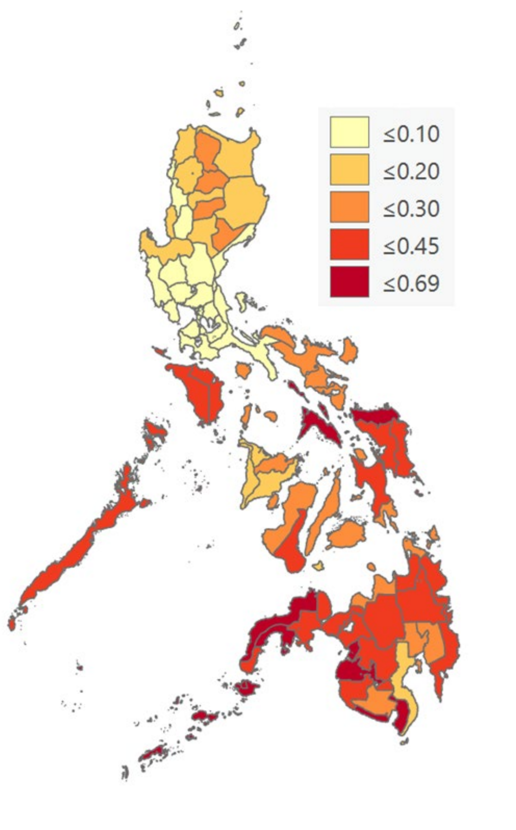
Married	78.37%	89.61%	81.11%	72.95%
Widowed	14.64%	8.58%	14.68%	16.94%
Divorced/Separated	2.63%	1.34%	2.11%	3.34%
Unknown	0.03%	0.01%	0.01%	0.04%
Head Highest Grade Completed				
No Grade	3.25%	9.01%	3.63%	0.90%
Elementary Undergraduate	22.10%	45.48%	28.92%	10.37%
Elementary Graduate	19.04%	24.59%	26.51%	13.86%
High School Undergraduate	12.10%	12.14%	16.70%	10.21%
High School Graduate	21.56%	7.87%	19.89%	27.48%
College Undergraduate	10.44%	0.84%	3.96%	16.76%
Bachelor	11.17%	0.06%	0.40%	19.81%
Post graduate	0.35%	0.00%	0.00%	0.62%
With Job/Business	16.45%	5.78%	11.92%	22.39%
Building type				
Single house	93.48%	99.06%	97.43%	89.74%
Duplex	2.68%	0.74%	1.74%	3.81%
Apartment/accessoria/condo/town house	3.52%	0.15%	0.71%	5.96%
Commercial/industrial/agricultural	0.27%	0.02%	0.08%	0.44%
Others	0.04%	0.03%	0.04%	0.05%
Building age	26.15	21.87	24.55	28.44
Roof type				
Strong material	73.17%	48.11%	65.73%	85.80%
Light material	16.60%	39.73%	21.75%	5.63%
Salvaged/makeshift materials	0.70%	1.03%	0.93%	0.48%
Mixed but predominantly strong material	6.62%	6.72%	7.64%	6.17%
Mixed but predominantly light materials	2.71%	4.04%	3.68%	1.81%
Mixed but predominantly salvaged materials	0.19%	0.36%	0.25%	0.10%
Others	0.01%	0.01%	0.02%	0.01%
Wall type				
Strong material	61.94%	32.91%	50.13%	77.87%
Light material	22.16%	48.90%	30.07%	8.68%
Salvaged/makeshift materials	1.04%	1.59%	1.44%	0.66%
Mixed but predominantly strong material	10.20%	9.42%	11.93%	9.79%
Mixed but predominantly light materials	4.38%	6.60%	6.07%	2.85%
Mixed but predominantly salvaged materials	0.27%	0.57%	0.34%	0.13%
Others	0.01%	0.00%	0.02%	0.01%

Toilet type				
Water-sealed	77.38%	41.15%	71.91%	93.49%
Closed pit	10.21%	24.30%	13.03%	3.66%
Open pit	5.05%	14.49%	5.98%	1.06%
Others	1.50%	3.10%	1.90%	0.73%
None	5.86%	16.96%	7.18%	1.06%
With Electricity	82.09%	45.12%	79.58%	97.27%
Source of water				
Own use, faucet, community water system	33.61%	4.09%	13.37%	53.18%
Shared, faucet, community water system	12.93%	16.02%	16.26%	10.39%
Own use, tubed/piped well	13.43%	6.24%	13.67%	16.09%
Shared, tubed/piped well	18.01%	28.83%	28.61%	9.54%
Dug well	9.81%	20.67%	13.77%	4.04%
Spring, river, stream, etc	7.21%	18.37%	8.75%	2.31%
Rain	2.15%	3.47%	2.94%	1.32%
Peddler	2.69%	2.15%	2.47%	2.99%
Others	0.15%	0.17%	0.17%	0.14%
Region				
Ilocos Region	5.65%	3.58%	7.38%	5.74%
Cagayan Valley	4.98%	3.92%	7.43%	4.39%
Central Luzon	7.87%	1.59%	5.75%	11.14%
Southern Tagalog Region	9.81%	1.77%	5.60%	14.61%
Bicol Region	5.83%	8.21%	7.97%	4.05%
Western Visayas	6.90%	7.02%	8.35%	6.25%
Central Visayas	6.41%	8.01%	7.86%	5.20%
Eastern Visayas	5.33%	9.37%	7.16%	3.05%
Zamboanga Peninsula	4.24%	9.11%	4.26%	2.37%
Northern Mindanao	4.65%	7.15%	4.92%	3.58%
Davao Region	5.61%	5.62%	6.14%	5.38%
SOCCSKSARGEN	5.14%	7.39%	5.77%	4.02%
National Capital Region	10.68%	0.29%	1.51%	18.40%
Cordillera Administrative Region	4.08%	2.84%	4.51%	4.38%
Autonomous Region in Muslim Mindanao	4.55%	11.67%	5.12%	1.59%
Caraga Region	4.26%	6.45%	5.72%	2.82%
Southwestern Tagalog Region	4.01%	6.02%	4.56%	3.01%

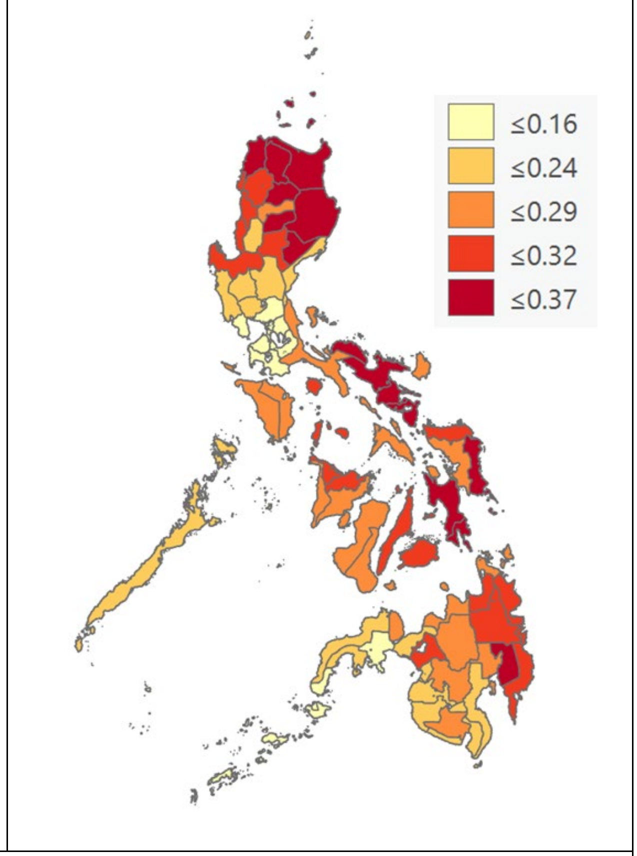
Figure 5 below presents the spatial distribution of chronic poverty for the purpose of comparing with the spatial distribution of vulnerability to poverty from typhoons (based on the 24.9% threshold).[24]

Figure 5: The spatial distribution of chronic poverty and Vulnerability to Poverty in the Philippines

(a) Chronic Poverty rate Map



(b) Non-poor Vulnerable to Poverty rate Map (based on 24.9% threshold)



Source: Bank staff estimates based on own estimates

One question of particular interest in the identification of those vulnerable to poverty is the extent to which those vulnerable to poverty are households that are just above the poverty line, and thus easily pushed below the poverty line in the event of an adverse shock, such as a typhoon. For operational purposes, the vulnerable population is typically identified by the group of households/individuals with per capita income or PCE above the poverty line and below the "vulnerability line" defined as a multiple of the poverty line. For example, in Indonesia, the vulnerable households are identified using a proxy means test (PMT) approach as the households that have predicted PCE that are above the poverty line and below the

[24] See Annex 6 for the corresponding figure using the 50% threshold.

vulnerability line defined as 1.5*Poverty Line. Along similar lines, in Brazil, the vulnerable population is identified by having a monthly per capita income above the poverty line of R$140 per capita per month and below the vulnerability line of R$291 (both lines in June 2011 prices). However, the extent to which per capita income or PCE prior to the incidence of shock are the best predictors of falling into poverty in the event of exposure to a shock is primarily an empirical issue.

Tables 8 and 9 below provide the detailed distribution of the households identified as vulnerable based on the two different thresholds, relative to the distance of their current PCE (prior to the shock) from the poverty line. Based on the 24.9% threshold, the total number of households classified as vulnerable to poverty (93,826 households) is considerably larger than the number of households vulnerable to poverty based on the 50% threshold in Table 9 (11,7123 households).

Table 8: Vulnerable to poverty defined as more than 24.9% probability of being poor

PL plus	1.1PL	1.2PL	1.3PL	1.4PL	1.5PL	1.5PL-
Frequency	20,848	21,244	20,170	18,731	11,347	1,504
Percent	22.22	22.64	21.49	19.96	12.09	1.60
Cumulation	22.22	44.85	66.35	86.31	98.40	100.00

Moreover, with the lower threshold, 22.22 % of the vulnerable to poverty are below 1.1 x Poverty Line (PL), 44.85% are below 1.2 x PL and 66.35 % are below 1.3 x PL (see Table 8 and figure 6a). In contrast, based on the 50% threshold, 95.91% of the vulnerable to poverty are below 1.1 x Poverty Line (PL), and 100% of the households vulnerable to poverty are below 1.2 x Poverty Line (PL) (see Table 9 see figure 6b).

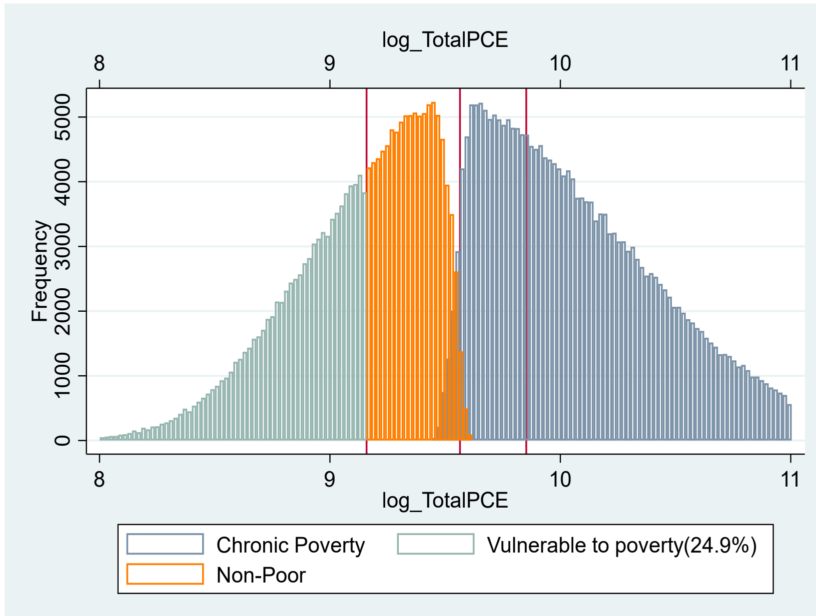
Table 9: Vulnerable to poverty defined as more than 50% probability of being poor

PL plus	1.1PL	1.2PL
Frequency	11,244	479
Percent	95.91	4.09
Cumulation	95.91	100

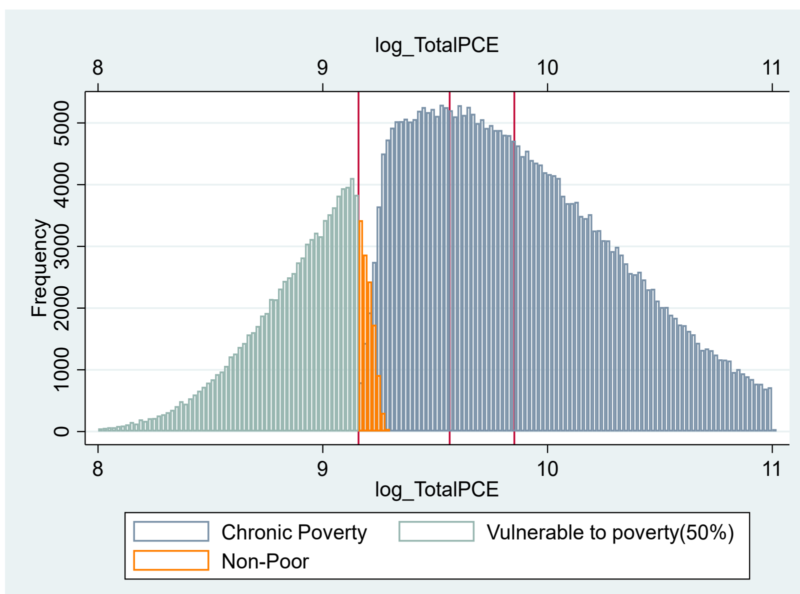
The above results serve to highlight the point that the identification of the vulnerable to poverty is a policy decision that involves much more than just technical considerations. The decision to support the vulnerable and the threshold used to determine who is vulnerable to poverty are intrinsically linked to the amount of budgetary resources available, as well as the ethical and political economy issues associated with the use of scarce financial resources to support households that are from higher parts of the welfare distribution.

Figure 6: The distribution of predicted PCE of the vulnerable to poverty and the poverty line.

(6a): Vulnerable to poverty based on the **24.9%** probability threshold



(6b): Vulnerable to poverty based on the **50%** probability threshold



5. Concluding remarks

This paper made significant progress towards (a) estimating the impacts of typhoons on household consumption; and (b) identifying ex-ante the households potentially vulnerable to poverty due to typhoons. A wind field model for the Philippines was employed to estimate local wind speeds at any particular locality where a tropical typhoon directly passes over or nearby. The estimated wind speeds from past typhoons were merged to contemporaneous household surveys (FIES) at the barangay level and consumption expenditures were then regressed against windspeed (or a related damage index) and socioeconomic household characteristics.

The estimates revealed that exposure of a barangay to a typhoon in the 6 months before the month of interview is associated with a statistically significant decline in total per capita expenditures and in specifically food and protein per capita expenditures. Expenditures on fruits and vegetables, cereals, education, medical services and nonfood items appear to be unaffected. These results are found to be robust to changes in the measure of the shock or to controlling for potential lagged effects, and unobserved household heterogeneity. The estimated coefficients from the regression model were also used to estimate ex-ante household vulnerability to poverty (i.e. the likelihood of household consumption falling below the poverty line) in the event of future natural disasters of different intensities.

It is important to bear in mind that the methodological framework employed in this paper for typhoons can also be employed with fairly minor modifications to identify the households vulnerable to poverty from a variety of other natural hazards. Models analogous to the wind field model for typhoons based on freely accessible remotely sensed data can be used for the estimation of the intensity of other natural hazards such as floods, earthquakes and even tsunamis (e.g., Skoufias, Strobl and Tveit, 2017). Thus, ex-ante estimates of the households vulnerable to poverty from floods and earthquakes can also be derived. Machine learning methods can also be used to improve the out-of-sample predictive ability of the regression models applied to retrospective data to estimate the relation between disaster intensity, welfare impacts, and household socio-economic characteristics. Finally, if the interest is on identifying the vulnerable to all kinds of covariate and idiosyncratic shocks, and not just to a specific shock as in this paper, it would be useful to explore and contrast the estimates of vulnerability to poverty obtained from alternative methods (e.g. the method proposed by Gunther and Harttgen, 2009).

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Annex 1: Estimated Headcount Poverty Rate (by year and year and semester)

Poverty rate by year

	2003	2006	2009	2012	2015
Poor=0	66,155	62,475	65,156	66,362	69,090
(%)	75.1	76.5	79.97	78.14	80.88
Poor=1	21,934	19,189	16,322	18,564	16,335
(%)	24.9	23.5	20.03	21.86	19.12

Poverty rate by year and semester

	2003-1	2003-2	2006-1	2006-2	2009-1	2009-2	2012-1	2012-2	2015-1	2015-2
Poor=0	34,535	31,620	31,569	30,906	32,888	32,268	33,420	32,942	35,266	33,824
(%)	75.5	74.66	76.7	76.3	80.3	79.63	78.38	77.9	80.37	81.42
Poor=1	11,204	10,730	9,588	9,601	8,069	8,253	9,219	9,345	8,616	7,719
(%)	24.5	25.34	23.3	23.7	19.7	20.37	21.62	22.1	19.63	18.58

Annex 2: Wind Field Model

We use Boose et al.'s (2004) version of the well-known Holland (1980) wind field model. More specifically, the wind experienced at time *t* due to hurricane *k* at any point *j*, i.e., $W_{j,k,t}$ is given by:

$$W_{j,k,t} = \mathrm{GF}\left[V_{m,k,t} - \mathrm{S}\left(1 - \sin\left(T_{j,k,t}\right)\right)\frac{V_{h,k,t}}{2}\right]\left[\frac{R_{m,k,t}}{R_{j,k,t}}^{B_P} exp\left(1 - \left[\frac{R_{m,k,t}}{R_{j,k,t}}^{B_P}\right]\right)\right]^{1/2} \qquad \text{(A1)}$$

where V_m is the maximum sustained wind velocity anywhere in the hurricane, T is the clockwise angle between the forward path of the hurricane and a radial line from the hurricane center to the pixel of interest, $P = j$, $V_{h,k,t}$ is the forward velocity of the hurricane, R_m is the radius of maximum winds, and R is the radial distance from the center of the hurricane to point *P*. The remaining ingredients in (A1) consist of the gust factor G and the scaling parameters $F, S,$ and B, for surface friction, asymmetry due to the forward motion of the storm, and the shape of the wind profile curve, respectively.

In terms of implementing (A1), one should note that it is given by the storm track data described in the data section, V_h can be directly calculated by following the storm's movements between locations along its track, and R and T are calculated relative to the point of interest *P=j*. All other parameters have to be estimated or assumed. For instance, we have no information on the gust wind factor G, but a number of studies (e.g., Paulsen and Schroeder, 2005) have measured G to be around 1.5, and we also use this value. For S we follow Boose *et al.* (2004) and assume it to be 1. While we also do not know the surface friction to directly determine F, Vickery et al. (2009) note that in open water the reduction factor is about 0.7 and reduces by 14% on the coast and 28% further 50 km inland. We thus adopt a reduction factor that linearly decreases within this range as we consider points *i* further inland from the coast. To determine B we employ Holland's (2008) approximation method, whereas we use the parametric model estimated by Xiao et al. (2009) to estimate R_{max}. Our source for hurricane track data is the HURDAT Best Track Data, which provides six hourly data on all tropical cyclones, including the position of the eye and the maximum wind speed of the storm. These tracks are linearly interpolated to hourly positions. Finally, as set of points, $j = 1, \ldots J$, we take the centroid of the barangay's PSG coordinates.

Annex 3: Table 1 with full set of regressors

	Total	Food	Non-Food	Protein	Fruit	Cereal	Education	Medical
f203_hy	-0.157***	-0.235***	-0.0621	-0.483***	-0.117	-0.0453	-0.111	-0.0981
	(-3.55)	(-5.32)	(-1.09)	(-6.83)	(-1.60)	(-1.25)	(-0.78)	(-0.71)
Family size	-0.116***	-0.0929***	-0.137***	-0.106***	-0.129***	-0.0615***	-0.122***	-0.153***
	(-193.33)	(-176.48)	(-183.90)	(-122.36)	(-169.45)	(-133.69)	(-56.31)	(-94.35)
Female headed	0.0286***	0.00942**	0.0419***	0.0274***	0.0626***	-0.0125***	0.313***	0.0555***
	(7.10)	(2.79)	(8.30)	(5.33)	(12.19)	(-4.16)	(19.34)	(4.63)
Household head age	0.0035***	0.00133***	0.0051***	0.0008***	0.0053***	0.0023***	0.0167***	0.0132***
	(32.88)	(14.64)	(37.40)	(5.54)	(37.84)	(28.38)	(39.59)	(38.75)
Marital status (Single Omitted)								
Married	-0.142***	-0.109***	-0.161***	0.0936***	0.0660***	-0.0623***	-0.357***	0.115***
	(-23.01)	(-20.49)	(-20.88)	(10.39)	(7.46)	(-11.70)	(-8.51)	(6.14)
Widowed	-0.164***	-0.112***	-0.197***	0.0571***	-0.0324***	-0.0793***	-0.796***	0.0283
	(-24.23)	(-19.32)	(-23.13)	(6.03)	(-3.49)	(-14.26)	(-18.52)	(1.36)
Divorced/Separated	-0.156***	-0.105***	-0.186***	-0.00135	-0.0636***	-0.0637***	-0.582***	-0.136***
	(-18.16)	(-13.99)	(-17.30)	(-0.11)	(-5.39)	(-9.09)	(-12.05)	(-5.07)
Unknown	0.0519	0.0266	0.0739	0.188**	0.0837	0.0353	-0.0687	0.266
	(0.75)	(0.51)	(0.88)	(2.66)	(1.09)	(0.93)	(-0.26)	(1.24)
Head Highest Grade (No grade omitted)								
Elementary incomplete	0.0606***	0.0428***	0.0935***	0.0915***	0.00883	0.0683***	0.121***	0.144***
	(7.49)	(5.46)	(8.88)	(6.43)	(0.67)	(7.68)	(4.61)	(6.29)
Elementary Graduate	0.125***	0.0917***	0.181***	0.177***	0.0608***	0.0903***	0.260***	0.265***
	(14.58)	(10.99)	(16.45)	(11.87)	(4.43)	(9.91)	(9.50)	(11.19)
High School incomplete	0.185***	0.131***	0.263***	0.229***	0.0829***	0.0967***	0.368***	0.390***
	(20.58)	(15.02)	(22.73)	(14.84)	(5.81)	(10.32)	(12.88)	(15.80)
High School Graduate	0.279***	0.192***	0.389***	0.314***	0.143***	0.104***	0.584***	0.502***
	(30.93)	(22.13)	(33.65)	(20.59)	(10.12)	(11.23)	(20.49)	(20.42)
College Incomplete	0.467***	0.303***	0.639***	0.452***	0.247***	0.132***	1.050***	0.745***
	(48.86)	(33.78)	(51.97)	(28.87)	(17.02)	(13.90)	(34.56)	(28.21)
Bachelor	0.780***	0.473***	1.035***	0.637***	0.428***	0.188***	1.570***	1.174***
	(73.25)	(49.87)	(76.89)	(39.76)	(28.75)	(19.60)	(49.03)	(42.85)
Post graduate	1.207***	0.670***	1.568***	0.839***	0.651***	0.247***	2.028***	1.922***
	(46.43)	(37.04)	(52.01)	(31.61)	(23.82)	(15.39)	(25.84)	(30.52)
With job	-0.00321	0.0246***	-0.0221***	-0.0122**	0.0519***	0.0439***	0.0158	-0.393***
	(-0.95)	(8.73)	(-5.13)	(-2.80)	(11.53)	(17.29)	(1.07)	(-36.19)
Building type (Single house omitted)								
Duplex	0.0456***	0.0425***	0.0511***	0.0458***	0.0189*	-0.00177	-0.0781**	0.0632**
	(6.39)	(6.92)	(5.62)	(5.09)	(1.98)	(-0.34)	(-2.98)	(3.07)
Apartment/accessoria/condo/townhouse	0.109***	0.0885***	0.132***	0.0651***	0.0262*	0.000032	0.180***	0.183***
	(12.80)	(13.54)	(12.42)	(6.51)	(2.33)	(0.01)	(5.91)	(8.31)
Commercial/industrial/agricultural	0.246***	0.174***	0.284***	0.0868*	0.110**	0.0525*	0.399***	0.331***
	(8.22)	(6.49)	(7.98)	(2.23)	(2.93)	(2.55)	(3.32)	(4.33)
Other	0.0233	0.0250	0.0212	0.0963	0.0923	-0.0595	-0.0506	0.107
	(0.51)	(0.57)	(0.36)	(1.29)	(1.20)	(-1.26)	(-0.26)	(0.56)
Type of wall (light material omitted)								
Strong material	0.160***	0.0925***	0.236***	0.130***	0.0632***	0.0342***	0.219***	0.241***
	(35.16)	(23.09)	(38.91)	(19.36)	(9.59)	(9.86)	(15.60)	(18.59)
Salvaged	0.00108	0.00683	0.00204	0.00901	-0.0445*	0.000425	-0.0673	-0.0212
	(0.10)	(0.65)	(0.14)	(0.52)	(-2.29)	(0.04)	(-1.59)	(-0.55)
Predominantly strong	0.0443***	0.0278***	0.0799***	0.0364***	-0.0112	0.0167***	0.0295	0.105***
	(8.40)	(5.79)	(11.43)	(4.55)	(-1.42)	(3.96)	(1.69)	(6.39)
Predominantly light	0.0118	0.0112	0.0229**	-0.00188	-0.0197	0.00881	-0.0346	0.0636**
	(1.77)	(1.81)	(2.63)	(-0.18)	(-1.86)	(1.59)	(-1.65)	(2.98)
Predominantly salvaged	0.0105	-0.00107	0.00485	-0.00484	-0.0739*	-0.0311	-0.0429	0.0279
	(0.45)	(-0.05)	(0.15)	(-0.12)	(-2.00)	(-1.56)	(-0.56)	(0.36)
Others	0.167	0.114	0.178	-0.00531	0.0952	0.112	-0.272	-0.0914
	(1.93)	(1.40)	(1.23)	(-0.02)	(0.62)	(1.21)	(-0.77)	(-0.22)
Type of roof (light material omitted)								

Strong material	0.0728***	0.0351***	0.129***	0.0361***	0.0254***	0.0324***	0.120***	0.1000***
	(15.36)	(8.38)	(20.28)	(5.03)	(3.56)	(8.33)	(7.99)	(7.60)
Salvaged	0.0123	0.0120	0.0189	-0.0228	0.0120	0.00904	0.0201	0.0368
	(0.73)	(0.78)	(0.84)	(-0.83)	(0.43)	(0.66)	(0.36)	(0.72)
Predominantly strong	0.0350***	0.0209***	0.0700***	0.0156	0.0405***	0.0231***	0.0659**	-0.00389
	(5.65)	(3.80)	(8.44)	(1.63)	(4.28)	(4.55)	(3.08)	(-0.20)
Predominantly light	0.0255**	0.0183*	0.0446***	0.0234	0.0332**	0.0118	0.0169	-0.0132
	(3.09)	(2.42)	(4.13)	(1.81)	(2.59)	(1.75)	(0.64)	(-0.51)
Predominantly salvaged	-0.0337	-0.00287	-0.0696	-0.0652	-0.0279	0.0179	-0.0170	-0.0166
	(-1.25)	(-0.11)	(-1.91)	(-1.37)	(-0.64)	(0.74)	(-0.19)	(-0.18)
Others	-0.00630	-0.0611	0.118	-0.153	-0.227	0.0202	0.635	0.187
	(-0.08)	(-0.79)	(1.07)	(-0.60)	(-1.65)	(0.24)	(1.80)	(0.44)
Quintile of Floor area (smallest omitted)								
Quintile 2	0.0677***	0.0388***	0.105***	0.0711***	0.0421***	0.0230***	0.112***	0.0793***
	(19.13)	(12.07)	(22.51)	(12.13)	(7.83)	(7.98)	(9.02)	(7.18)
Quintile 3	0.155***	0.0828***	0.231***	0.131***	0.0980***	0.0434***	0.305***	0.191***
	(36.63)	(22.06)	(42.10)	(20.56)	(15.57)	(13.36)	(20.74)	(14.31)
Quintile 4	0.317***	0.161***	0.448***	0.234***	0.189***	0.0721***	0.535***	0.447***
	(57.93)	(37.18)	(63.83)	(32.71)	(27.18)	(19.77)	(33.14)	(30.57)
Largest	0.507***	0.262***	0.694***	0.366***	0.322***	0.135***	0.837***	0.608***
	(48.28)	(36.09)	(53.92)	(33.71)	(29.00)	(21.73)	(31.65)	(26.70)
Quintile of Built year (oldest omitted)								
Quintile 2	0.0355***	0.0211***	0.0471***	0.0200***	0.0339***	0.0205***	0.185***	-0.0382***
	(9.75)	(6.89)	(10.18)	(4.23)	(7.16)	(8.05)	(12.93)	(-3.50)
Quintile 3	0.0250***	0.0127***	0.0343***	0.00749	0.0263***	0.0143***	0.141***	-0.0388***
	(6.15)	(3.73)	(6.58)	(1.42)	(5.02)	(5.15)	(9.45)	(-3.29)
Quintile 4	0.0187***	0.00810*	0.0240***	0.00797	0.0314***	0.00907**	0.0295*	0.00286
	(4.62)	(2.35)	(4.61)	(1.48)	(5.80)	(3.07)	(2.00)	(0.24)
Newest	0.0165***	0.00477	0.0204***	0.000642	0.0427***	0.0151***	0.000247	-0.0224
	(3.84)	(1.27)	(3.73)	(0.10)	(7.07)	(4.72)	(0.02)	(-1.69)
Toilet type (None omitted)								
Water-sealed	0.140***	0.0976***	0.198***	0.167***	0.175***	0.0382***	0.316***	0.101***
	(20.63)	(15.33)	(21.97)	(14.17)	(14.34)	(6.42)	(16.52)	(5.46)
Closed pit	0.0291***	0.0230**	0.0407***	0.0369**	0.140***	0.0252***	0.183***	-0.132***
	(3.86)	(3.19)	(4.10)	(2.72)	(10.18)	(3.76)	(8.26)	(-6.15)
Open pit	0.0166*	0.0154	0.0173	0.0126	0.128***	0.0209**	0.150***	-0.0713**
	(1.97)	(1.90)	(1.51)	(0.83)	(8.19)	(2.71)	(5.86)	(-2.85)
Others	0.0703***	0.0606***	0.0867***	0.154***	0.161***	-0.0320**	0.165***	0.0111
	(5.34)	(4.82)	(5.02)	(6.62)	(6.83)	(-2.83)	(4.41)	(0.32)
Without Electricity	-0.188***	-0.122***	-0.288***	-0.191***	-0.0410***	-0.0598***	-0.199***	-0.238***
	(-40.84)	(-28.78)	(-47.73)	(-24.31)	(-5.60)	(-15.91)	(-13.53)	(-18.15)
Water source (Spring, river, stream, etc. omitted)								
Own use, faucet, community water system	0.315***	0.210***	0.424***	0.319***	0.118***	0.0452***	0.474***	0.412***
	(34.62)	(26.54)	(35.24)	(23.25)	(9.25)	(6.69)	(19.65)	(17.69)
Shared, faucet, community water system	0.0758***	0.0704***	0.0995***	0.118***	-0.0402**	-0.00109	-0.000202	0.117***
	(8.59)	(8.89)	(8.58)	(8.45)	(-3.13)	(-0.16)	(-0.01)	(5.10)
Own use tubed/piped well	0.157***	0.105***	0.218***	0.184***	0.0373**	0.0452***	0.261***	0.235***
	(17.39)	(13.24)	(18.30)	(13.23)	(2.91)	(6.43)	(10.43)	(9.59)
Shared, tubed/piped well	0.0208*	0.0301***	0.0215	0.0629***	-0.0570***	0.00739	-0.0483*	0.0475*
	(2.50)	(4.05)	(1.94)	(4.73)	(-4.63)	(1.07)	(-2.13)	(2.10)
Dug well	0.0631***	0.0665***	0.0638***	0.143***	0.0101	0.0214**	0.0842***	0.0763**
	(6.89)	(7.95)	(5.24)	(9.07)	(0.74)	(2.79)	(3.30)	(3.06)
Rain	0.0376*	0.0378**	0.0404*	0.0982***	-0.0166	0.0143	0.0375	0.0879*
	(2.53)	(2.83)	(2.15)	(4.16)	(-0.75)	(1.39)	(0.81)	(2.18)
Peddler	0.171***	0.150***	0.216***	0.239***	0.0108	0.0169	-0.0652	0.204***
	(13.33)	(13.03)	(12.51)	(10.81)	(0.53)	(1.58)	(-1.53)	(6.04)
Other	0.144***	0.102***	0.184***	0.150***	0.0481	-0.0205	0.147	0.211**
	(5.59)	(4.38)	(5.18)	(3.84)	(0.86)	(-0.80)	(1.64)	(2.72)
adj. R2	0.632	0.504	0.635	0.384	0.305	0.171	0.298	0.227
N	412286	412268	412286	410242	410149	411118	255586	355402

Note: Regressions include a complete set of semester, year, and region interaction dummies. (not shown). *** p<0.01, ** p<0.05, * p<0.1.

Annex 4: The impacts of typhoons on PCE and access to 4Ps controlling for household unobserved heterogeneity

a: Random-effects specification								
Using a binary variable on windspeed including interaction								
f203_hy	0.0513	-0.0295	0.0905	-0.157*	0.0908	-0.0294	-0.00111	0.0942
	(1.12)	(-0.61)	(1.58)	(-2.15)	(1.10)	(-0.67)	(-0.01)	(0.58)
4Ps	-0.0964***	-0.069***	- 0.142***	-0.154***	-0.042***	- 0.00055	- 0.0547**	-0.114***
	(-19.95)	(-15.43)	(-21.87)	(-19.92)	(-5.63)	(-0.13)	(-3.26)	(-6.95)
f203_hy x 4Ps	-0.0350	0.0300	-0.0793	0.0172	-0.0135	0.0265	-0.228	-0.0687
	(-0.93)	(0.77)	(-1.58)	(0.26)	(-0.22)	(0.58)	(-1.45)	(-0.43)
R2 overall	0.618	0.474	0.628	0.349	0.279	0.134	0.276	0.245
N	167960	167956	167960	167134	167275	167558	100366	144019
Using a binary variable on windspeed including interaction								
W119_hy	-0.0169	-0.0256*	-0.0149	- 0.0735***	-0.00393	0.00167	0.0516	0.00479
	(-1.63)	(-2.23)	(-1.16)	(-3.79)	(-0.19)	(0.16)	(1.50)	(0.12)
4Ps	-0.0984***	- 0.0696***	- 0.144***	-0.153***	- 0.0393***	- 0.00210	-0.0395*	-0.103***
	(-19.84)	(-15.18)	(-21.52)	(-19.22)	(-5.01)	(-0.45)	(-2.28)	(-6.08)
W119_hy x 4Ps	0.00532	0.00936	0.000158	0.000892	-0.0151	0.0103	- 0.107***	-0.0582
	(0.81)	(1.33)	(0.02)	(0.07)	(-1.28)	(1.32)	(-3.69)	(-1.93)
R2 overall	0.618	0.474	0.628	0.349	0.279	0.134	0.276	0.245
N	167960	167956	167960	167134	167275	167558	100366	144019
b: Fixed-effects specification								
Using a binary variable on windspeed including interaction								
f203_hy	0.125*	0.0776	0.159*	0.0189	0.240*	0.0144	-0.00156	0.383*
	(2.50)	(1.43)	(2.57)	(0.23)	(2.49)	(0.29)	(-0.01)	(2.02)
4Ps	0.0381**	0.0247	0.0627***	0.0218	0.0339	0.0201	0.109*	0.198**
	(3.05)	(1.81)	(3.88)	(1.00)	(1.39)	(1.23)	(1.99)	(3.07)
f203_hy x 4Ps	-0.0826	-0.0503	-0.125*	-0.0732	-0.132	-0.0589	-0.432*	-0.196
	(-1.80)	(-0.99)	(-2.12)	(-0.83)	(-1.52)	(-0.94)	(-2.35)	(-0.87)
R2 overall	0.282	0.221	0.290	0.182	0.187	0.0970	0.0659	0.0549
N	167960	167956	167960	167134	167275	167558	100366	144019
Using a binary variable on windspeed including interaction								
W119_hy	0.0125	0.0117	0.0178	-0.000284	0.0192	0.0112	0.0632	0.110*
	(1.14)	(0.94)	(1.30)	(-0.01)	(0.81)	(0.94)	(1.65)	(2.50)
4Ps	0.0353**	0.0229	0.0592***	0.0206	0.0343	0.0197	0.115*	0.201**
	(2.81)	(1.68)	(3.63)	(0.95)	(1.40)	(1.21)	(2.09)	(3.11)

W119_hy x 4Ps	0.0141	0.00907	0.0152	0.000711	-0.0178	-0.00397	-0.110**	-0.0476
	(1.83)	(1.05)	(1.43)	(0.05)	(-1.14)	(-0.38)	(-3.19)	(-1.15)
R2 overall	0.283	0.223	0.291	0.181	0.186	0.0970	0.0642	0.0583
N	167960	167956	167960	167134	167275	167558	100366	144019

Notes: Additional explanatory variables included but not reported here: family size, head is female, age of head, marital status of head, education level of head, head has a job, building type (single house vs, apartment etc.), type of material for roof, type of material for wall, floor area, type of toilet, water source, and separate binary variables for semester, year, and region, along with a complete set of interactions among these binary variables. Standard errors are corrected for clustering at the barangay level.

Annex 5:

Table A: Estimates of equation (1) including the maximum value of the damage index *f* over the 1950-2016 period for the barangay where a household is located.

	PCE Total (1)	PCE on Food (2)	PCE Non-Food (3)	PCE Protein (4)	PCE Fruit (5)	PCE Cereal (6)	PCE Education (7)	PCE Medical (8)
f203_hy	-0.168***	-0.255***	-0.0645	-0.509***	-0.139	-0.0483	-0.110	-0.112
	(-3.78)	(-5.74)	(-1.14)	(-7.20)	(-1.89)	(-1.33)	(-0.77)	(-0.81)
F203_max	0.109**	0.204***	0.0250	0.268***	0.221***	0.0307	-0.00883	0.162
	(3.22)	(6.59)	(0.59)	(5.84)	(4.61)	(1.31)	(-0.11)	(1.91)

Table B: Estimates of equation (1) based on the sub-sample of households appearing in both semesters

	PCE Total (1)	PCE on Food (2)	PCE Non-Food (3)	PCE Protein (4)	PCE Fruit (5)	PCE Cereal (6)	PCE Education (7)	PCE Medical (8)
f203_hy	-0.152***	-0.232***	-0.0536	-0.473***	-0.104	-0.0431	-0.114	-0.104
	(-3.44)	(-5.28)	(-0.94)	(-6.73)	(-1.43)	(-1.19)	(-0.80)	(-0.75)

Annex 6: The profile of the Chronic Poor and those Vulnerable to Poverty (based on the 24.9% threshold)

Summary statistics	Total	Chronic poor (21.4%)	Non-poor Vulnerable to poverty (2.8%)	Non-poor (75.8%)
Total adjusted Expenditure per capita	19,283	7,214	9,899	23,044
P4 Beneficiaries	18.5%	49.2%	34.8%	10.1%
Family Size	4.73	6.49	5.42	4.20
Age of Household head	49.06	45.35	48.20	50.14
Female headed	19.50%	8.38%	13.39%	22.87%
Head marital status				
Single	4.33%	0.46%	1.28%	5.54%
Married	78.37%	89.61%	83.44%	75.01%
Widowed	14.64%	8.58%	13.39%	16.40%
Divorced/Separated	2.63%	1.34%	1.87%	3.02%
Unknown	0.03%	0.01%	0.02%	0.03%
Head Highest Grade Completed				
No Grade	3.25%	9.01%	3.92%	1.60%
Elementary Incomplete	22.10%	45.48%	35.12%	15.01%
Elementary Graduate	19.04%	24.59%	28.39%	17.12%
High School Incomplete	12.10%	12.14%	15.74%	11.95%
High School Graduate	21.56%	7.87%	14.68%	25.68%
College Incomplete	10.44%	0.84%	2.05%	13.46%
Bachelor	11.17%	0.06%	0.11%	14.72%
Post graduate	0.35%	0.00%	0.00%	0.46%
With Job/Business	16.45%	5.78%	10.21%	19.70%
Building type				
Single house	93.48%	99.06%	98.21%	91.73%
Duplex	2.68%	0.74%	1.31%	3.28%
Apartment/accessoria/condo/town house	3.52%	0.15%	0.43%	4.59%
Commercial/industrial/agricultural	0.27%	0.02%	0.03%	0.35%
Others	0.04%	0.03%	0.03%	0.05%
Building age	26.15	21.87	23.91	27.44
Roof type				
Strong material	73.17%	48.11%	60.80%	80.71%
Light material	16.60%	39.73%	26.44%	9.69%
Salvaged/makeshift materials	0.70%	1.03%	0.84%	0.61%

Mixed but predominantly strong material	6.62%	6.72%	7.61%	6.56%
Mixed but predominantly light materials	2.71%	4.04%	3.97%	2.29%
Mixed but predominantly salvaged materials	0.19%	0.36%	0.33%	0.13%
Others	0.01%	0.01%	0.03%	0.01%
Wall type				
Strong material	61.94%	32.91%	46.17%	70.73%
Light material	22.16%	48.90%	33.77%	14.17%
Salvaged/makeshift materials	1.04%	1.59%	1.39%	0.87%
Mixed but predominantly strong material	10.20%	9.42%	11.71%	10.36%
Mixed but predominantly light materials	4.38%	6.60%	6.58%	3.68%
Mixed but predominantly salvaged materials	0.27%	0.57%	0.38%	0.18%
Others	0.01%	0.00%	0.01%	0.01%
Toilet type				
Water-sealed	77.38%	41.15%	64.80%	88.08%
Closed pit	10.21%	24.30%	14.95%	6.05%
Open pit	5.05%	14.49%	7.23%	2.30%
Others	1.50%	3.10%	1.83%	1.04%
None	5.86%	16.96%	11.18%	2.52%
With Electricity	82.09%	45.12%	71.61%	92.92%
Source of water				
Own use, faucet, community water system	33.61%	4.09%	8.67%	42.89%
Shared, faucet, community water system	12.93%	16.02%	16.86%	11.91%
Own use, tubed/piped well	13.43%	6.24%	11.28%	15.55%
Shared, tubed/piped well	18.01%	28.83%	31.91%	14.43%
Dug well	9.81%	20.67%	15.70%	6.52%
Spring, river, stream, etc	7.21%	18.37%	10.47%	3.94%
Rain	2.15%	3.47%	2.85%	1.75%
Peddler	2.69%	2.15%	2.14%	2.87%
Others	0.15%	0.17%	0.13%	0.15%
Region				
Ilocos Region	5.65%	3.58%	7.75%	6.16%
Cagayan Valley	4.98%	3.92%	11.31%	5.05%
Central Luzon	7.87%	1.59%	4.56%	9.77%
Southern Tagalog Region	9.81%	1.77%	4.26%	12.29%
Bicol Region	5.83%	8.21%	13.04%	4.89%
Western Visayas	6.90%	7.02%	8.28%	6.81%
Central Visayas	6.41%	8.01%	9.58%	5.84%

Eastern Visayas	5.33%	9.37%	13.96%	3.87%
Zamboanga Peninsula	4.24%	9.11%	0.82%	3.00%
Northern Mindanao	4.65%	7.15%	2.20%	4.03%
Davao Region	5.61%	5.62%	3.81%	5.67%
SOCCSKSARGEN	5.14%	7.39%	1.53%	4.64%
National Capital Region	10.68%	0.29%	0.90%	13.98%
Cordillera Administrative Region	4.08%	2.84%	6.43%	4.34%
Autonomous Region in Muslim Mindanao	4.55%	11.67%	1.73%	2.64%
Caraga Region	4.26%	6.45%	7.09%	3.53%
Southwestern Tagalog Region	4.01%	6.02%	2.75%	3.49%

Figure 6.1: The spatial distribution of the Vulnerable to Poverty in the Philippines (using the 50% threshold)